5.4 Measurement Sampling Rates for Daily Maximum and Minimum Temperatures

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1. INTRODUCTION

The maximum and minimum temperatures are two of the most important climate variables. With the establishment of new surface climate networks or the upgrade of existing networks, the selection of sampling rates relevant to the determination of maximum and minimum temperature is critical. Although the time constant of the sensor or the sensor and shield together will determine the shape of the continuous temperature curve, it is how this curve is sampled that determines differences in two series of discrete measurements. Thus, the maximum and minimum of the one-minute samples may differ from the maximum and minimum of one-second samples. This paper will present the effects of sampling rate on the observations of maximum and minimum air temperatures in several surface networks including the U. S. Climate Reference Networks (USCRN), the Cooperative Observing Program (COOP), and the automated weather station networks (AWS).

The issue of sampling rate for air temperature measurements usually is related to the time constant of temperature sensor and temperature radiation shield. We often found this issue was discussed in the atmospheric turbulence study (Kaimal and Finnigan, 1994) but hardly found in the surface climate observations. The reason for this might be because that the past air temperature measurements in surface climate networks were monitored by an analog liquid-in-glass (LIG) thermometer and its observations were digitized by observers in a virtually instantaneous way at specific observation times. Starting from1980s, numbers of electrical temperature sensors were started to use in current climate networks, for examples, an MMTS thermistor used in the COOP networks, a platinum resistance thermometer (PRT) used in the ASOS network, and a PRT used in the USCRN network, but the sampling rates of air temperature measurements to obtain the daily maximum and daily minimum temperature in above networks are quite different. In the COOP network, the MMTS readout takes readings approximately each 2 seconds for daily maximum and minimum temperatures. The ASOS 1088 hygrothermometer takes five-minute running average of one-minute average based on approximately ten-second sampling rate; the USCRN takes observations each five-second and takes five-minute discrete average to obtain daily maximum and minimum temperatures. Therefore, Our intend in this study is to investigate the temperature differences or biases of daily maximum and minimum air temperatures caused by different sampling rates and different averaging algorithms.

Assuming that a digital thermometer for obtaining temperature readings is to digitize a given continuous air temperature curve, thus, this digitization implies its replacement by discrete data points, equally spaced along the abscissa. Based on the Taylor series expansion method for any continuous curve, the errors in fitting that given curve by digital data can be expressed in terms of time interval and the second derivative of air temperature as follow (Bath, 1974),

$$|\delta T|_{max} \approx \frac{(\Delta t)^2}{8}\left|\frac{d^2 T_{air}}{dt^2}\right|_{max}$$

where δT, Δt, T_{air}, and t are the digitizing error, time interval of sampling, air temperature, and time. Therefore, the higher sampling rates and smaller change rates of air temperature changes, the smaller the digitizing errors and vice versa. Considering the requirement of sampling climate signal without loss of information of air temperature signals, the Nyquist frequency is usually referred to be a reference for determining a sampling rate in most meteorological and climatological applications. Based on the recommendations provided by the World Meteorological Organization (WMO) (WMO, 1996), for sampling extremes of meteorological variables, the samples should be taken at rates at least four times as fast as the time constant of

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temperature sensors. Although the time constant of any air temperature sensor has to be specified under a given wind speed condition, the reference sampling rate in our study used was taken in each two seconds because the USCRN temperature system is an aspirated system. In this study, we examined the daily maximum and minimum temperature differences due to different averaging algorithms of daily maximum and minimum temperature.

2. EXPERIMENTAL MEASUREMENTS

The experimental measurements in our test bed were conducted from July 2004 to October 2004 at the University of Nebraska's Horticulture Experiment Site (40°83' N, 96°67' W, elevation 383m). The ground surface height was maintained at about 8 cm by mowing.

In this study, two USCRN PRT temperature sensors were installed inside the USCRN radiation shield and the Cotton Region Shelter (CRS), respectively. An HMP45C temperature and relative humidity sensor was housed in the Gill radiation shield which configuration is commonly used in the automated weather station network. Therefore, three temperature systems included in this study are, USCRN sensor plus USCRN shield, USCRN sensor plus CRS, and HMP45C plus Gill shield. All temperature measurements were taken by using a CR23X data logger (Campbell Scientific. Inc.) and were sampled each two seconds. There were six types of daily maximum air temperature (Tmax) and daily minimum air temperature (Tmin) observed in this study in terms of different averaging algorithms (Table 1). The descriptions of different averaging daily Tmax and Tmin were listed in Table 1. All temperature sensors were newly calibrated immediately before the measurement period began. In our study, the Tmax and Tmin difference or bias is defined as the Tmax or Tmin difference relative to the daily Tmax or Tmin obtained from observations in a two-second sampling rate.

Currently data were available for 90 days during our observations. Since only minute-data were continuously collected in the CR23X data logger the calculation of the second derivatives of ambient temperature was derived from six minute observations which was centered by the time of daily Tmax or Tmin occurrence in terms of two-second observations.

3. PRELIMINARY RESULTS AND DISCUSSION

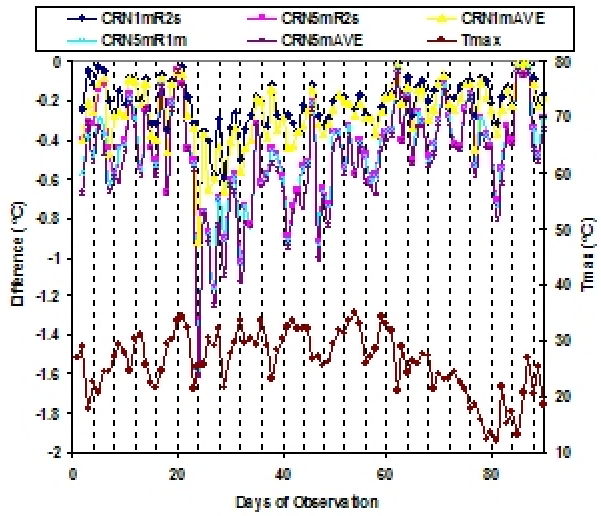

Fig. 1. Daily Tmax differences/biases in the USCRN temperature system due to five different averaging algorithms (CRN1mR2s, CRN5mR2s, CRN1mAVE, CRN5mR1m, and CRN5mAVE).

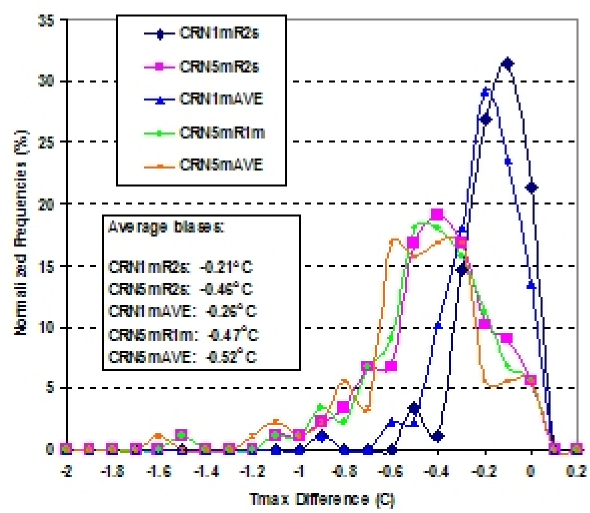

Fig. 2. Normalized frequencies of Tmax differences in the USCRN.

Figure 1 shows a time series of daily Tmax differences in the USCRN temperature system for all observations. All Tmax differences were negative and it indicates that a cooling bias existed in all of Tmax averaging algorithms. The CRN1mR2s and CRN1mAVE were relatively close to the reference Tmax (CRN2s) but all five-minute averaging methods had a larger cooling bias especially for the

CRN5mAVE, which algorithm is currently used in the official USCRN operations. The normalized frequency distributions of each Tmax difference were shown in Fig. 2. The results indicates that the five-minute discrete average had the largest cooling bias and the one-minute running average of each two-second sample was the smallest cooling bias. On the 90-day averages, the average cooling biases were -0.21, -0.28, -0.47, -0.48, and -0.62 ^{o}C, respectively for the CRN1mR2s, CRN1mAVE, CRN5mR1m, CRN5mR2s, and CRN5mAVE. Apparently, any five-minute averaging algorithm might not be acceptable for a high quality surface climate network because the result from our 90-day experiments is equivalent to a seasonal average of Tmax observations and the cooling bias over one degree in centigrade was not uncommon for the Tmax (Fig. 1). Note that in the official ASOS operation system, a five-minute running average algorithm (equivalent to the CRN5R1m in this study) is used for obtaining the Tmax. However, this Tmax algorithm still could introduce about half-degree C cooling bias on three-month average.

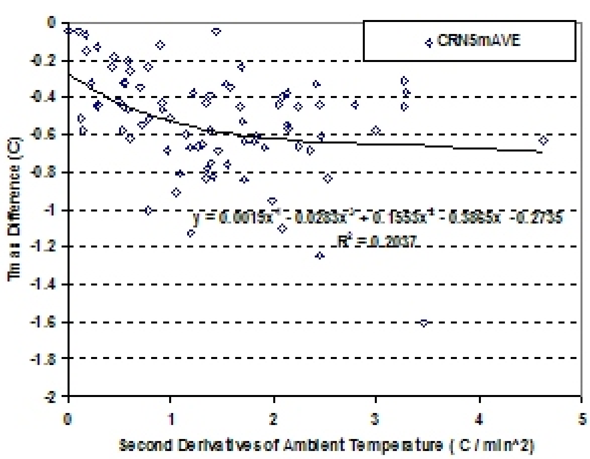

Fig. 3. Variations of daily Tmax differences (between the CRN5mAVE and CRN2s) with changes of the second derivative of ambient temperature in the USCRN temperature system.

With limited observation days, Figure 3 shows the variations of daily Tmax differences. In general, the Tmax cooling bias increased with increases of the second derivative of ambient temperature. Note that the X axis in Fig. 3 refers to a summation of absolute second-derivative value of six consecutive minutes. Our intend is to find a way to reveal the relation between the Tmax cooling bias and the change rates of ambient temperature change. It should be noted that the result in this paper is preliminary and more explicit analysis will be conducted when the number of observation day increases.

For the daily Tmin differences, the warming bias/difference was much more than the cooling bias in a time series of daily Tmin difference (Fig. 4). However, the magnitudes of daily Tmin differences were relatively smaller than the Tmax differences.

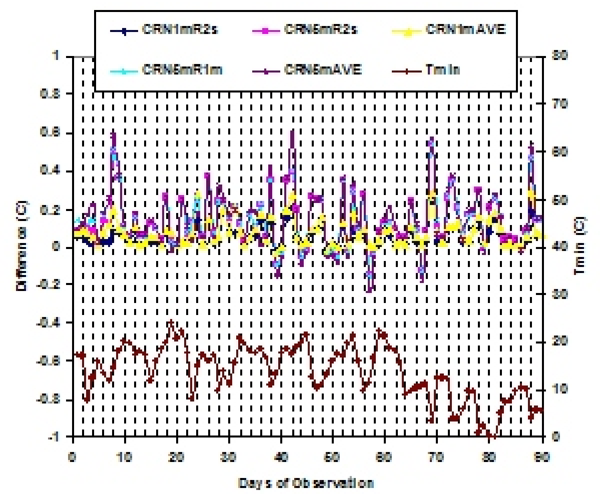

Fig. 4. As for Fig.1, but for daily Tmin differences/biases in the USCRN temperature system.

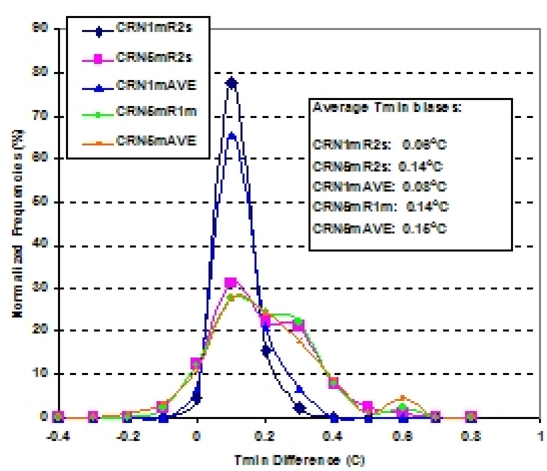

Fig. 5. Normalized frequencies of Tmin differences in the USCRN.

It is clear that one-minute averaging algorithms were better than five-minute averaging algorithms (Figs. 4 and 5). On average, all Tmin differences were positive which suggests that current Tmin algorithms for the USCRN and ASOS might be encountered a warming bias for daily Tmin records. Therefore, the variations of daily Tmin differences increased with the increases of the second derivative of ambient temperature (Fig. 6).

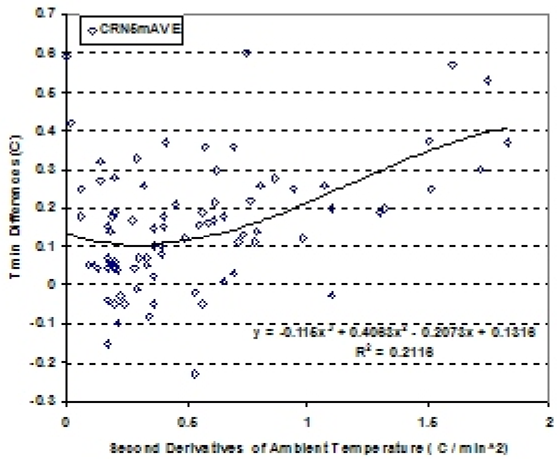

Fig. 6. Variations of daily Tmin differences (between the CRN5mAVE and CRN2s) with changes of the second derivative of ambient temperature in the USCRN temperature system.

Due to the space limitations, the preliminary results for the USCRN PRT sensor in the CRS are not shown, but are similar to the USCRN system for both Tmax and Tmin. However, two time series of daily Tmax and Tmin for the HMP45C sensor housed in the Gill shield were shown in Figure 7. It is obvious that the Tmax and Tmin differences for the HMP45C system were much smaller than the USCRN system and the system equipped with USCRN PRT sensor housed in the CRS. Therefore, the time constant of temperature sensor plays a more important role to response the Tmax and Tmin. The larger the time constant of temperature sensors, the longer the time integration/average is inherently embedded. In other words, the high frequency temperature variations are insensitive to the temperature sensor having a larger time constant. Therefore, for surface temperature homogeneity adjustment from earlier CRS with LIG thermometers to the current USCRN PRT sensors, it is necessary to evaluate the effects of time constant of temperature sensors used in historical climate data sets.

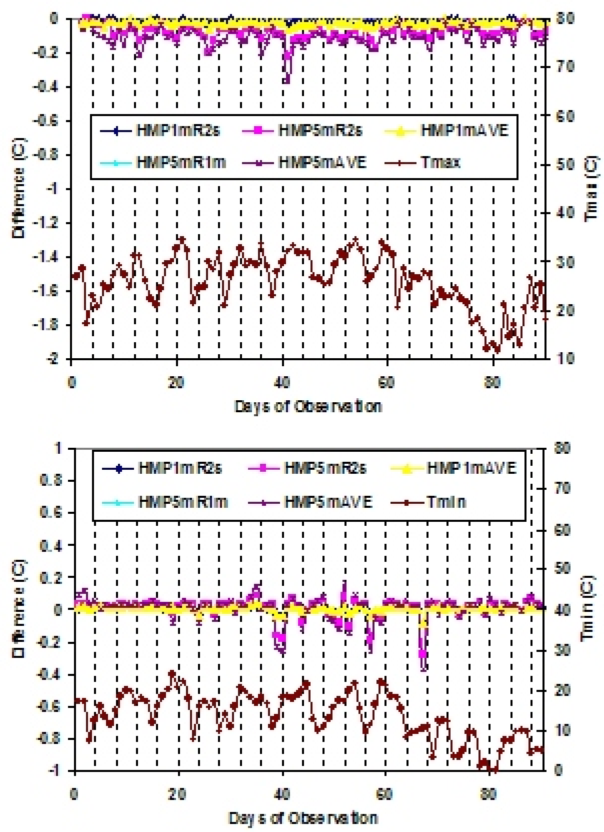

Fig. 7. Daily Tmax (top panel) and Tmin (bottom panel) differences/biases in the HMP45 temperature system due to five different averaging algorithms (HMP1mR2s, HMP5mR2s, HMP1mAVE, HMP5mR1m, and HMP5mAVE).

4. SUMMARY AND CONCLUSIONS

During the CRS era, the official LIG thermometer is about 60 seconds (refers to 3 m s^{-1} ventilation rate, 63% response) with an instantaneous reading for Tmax and Tmin but during the MMTS era, the time constant of MMTS sensor is approximately 20 seconds with a two-second sampling rate. Up to the date, the USCRN sensor has a similar time constant to the MMTS sensor but with a five-minute discrete average for calculating Tmax and Tmin. Without any doubt, these changes of time constant of temperature sensors, sampling rates, daily Tmax and Tmin averaging algorithms will introduce the uncertainties in the daily Tmax and Tmin climate data. In this study, over 0.5 ^{o}C average difference was detected for the Tmax and about 0.15 ^{o}C average difference for the Tmin in the USCRN temperature system. Therefore, the MMTS Tmax/Tmin might be higher/lower than the CRS by the LIG if only considering sampling issues although the statistical results shows totally different (Quayle et al., 1991). The statistical results in Quayle's work includes all uncertainties between the CRS and the MMTS such as the solar radiation and wind speed effects, and embedded electrical and sensor errors (Hubbard and Lin 2002, Hubbard et al., 2004, Lin and Hubbard 2004). In the HMP45C sensor housed in the Gill shield, the corresponding differences were less than 0.2 ^{o}C because of larger time constant for the HMP45C sensor. The Tmax and Tmin differences caused by different sampling rates and different averaging algorithms increased with increases of the second derivatives of ambient temperatures and they were strongly associated with the time constant of each temperature system.

REFERENCES

Bath, M, 1974: Sepctral Analysis in Geophysics. Oxford, New York.

Kaimal, J. C., and J. J. Finnigan, 1994: Atmospheric Boundary Layer Flows, 289pp., Oxford Univ. Press, New York.

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Hubbard, K. G. and X. Lin, 2002: Realtime data filtering models for air temperature measurements. *Geophysical Research Letters*. **29(10)**: 67-1:67-4.

Hubbard, K.G., X. Lin, C.B. Baker, and B. Sun, 2004: Air temperature comparison between the MMTS and the USCRN temperature systems. *J. Atmos and Oceanic Technology*, **21(10)**:1590-1597.

Quayle R. G., D. R. Easterling, T. R. Karl, and P. Y. Hughes,1991: Effects of recent thermometer changes in the Cooperative station network. *Bull. Amer. Meteor. Soc.*, **72**:1718-1723.

Lin, X. and K. G. Hubbard, 2004: Sensor and electronic biases/errors in air temperature measurements in common weather station networks. *J. Atmos. Oceanic Tech.*, **7**:1025-1032.

WMO, 1996: Guide to meteorological instruments and methods of observation. Sixth Edition. WMO-No.8, Geneva, Switzerland. *World Meteorological Organization*.

Table 1. Different daily Tmax and Tmin averaging algorithms based on the two-second sampling rate in the USCRN system, CRS system, and Gill system with an HMP45C sensor.

Daily Tmax or Tmin	Descriptions (Sensor plus Shield)
CRN2s	Sampling rate 2 secs (**CRN PRT in CRN**) (as a reference)
CRN1mR2s	1 minute running average of 2-second-data (CRN PRT in CRN)
CRN5mR2s	5 minute running average of 2-second-data (CRN PRT in CRN)
CRN1mAVE	1 minute discrete average of 2-second-data (CRN PRT in CRN)
CRN5mR1m	5 minute running average of 1-minute-discrete-data (CRN PRT in CRN)
CRN5mAVE	5 minute discrete average of 1-minute-discrete-data (CRN PRT in CRN)
CRS2s	Sampling rate 2 secs (**CRN PRT in CRS**) (as a reference)
CRS1mR2s	1 minute running average of 2-second-data (CRN PRT in CRS)
CRS5mR2s	5 minute running average of 2-second-data (CRN PRT in CRS)
CRS1mAVE	1 minute discrete average of 2-second-data (CRN PRT in CRS)
CRS5mR1m	5 minute running average of 1-minute-discrete-data (CRN PRT in CRS)
CRS5mAVE	5 minute discrete average of 1-minute-discrete-data (CRN PRT in CRS)
HMP2s	Sampling rate 2 secs (**HMP45 in Gill**) (as a reference)
HMP1mR2s	1 minute running average of 2-second-data (HMP45 in Gill)
HMP5mR2s	5 minute running average of 2-second-data (HMP45 in Gill)
HMP1mAVE	1 minute discrete average of 2-second-data (HMP45 in Gill)
HMP5mR1m	5 minute running average of 1-minute-discrete-data (HMP45 in Gill)
HMP5mAVE	5 minute discrete average of 1-minute-discrete-data (HMP45 in Gill)